Weekly Updates – Vinayak Gajendra Panchal

PART-1: Univariate Analysis of vehicle parameters

I conducted two sets of simulations using SUMO for the purpose of conducting ablation studies. In one set, 30% of the vehicles did not adhere to the rules, meaning their parameters were altered. In the other set, this percentage was increased to 50%.

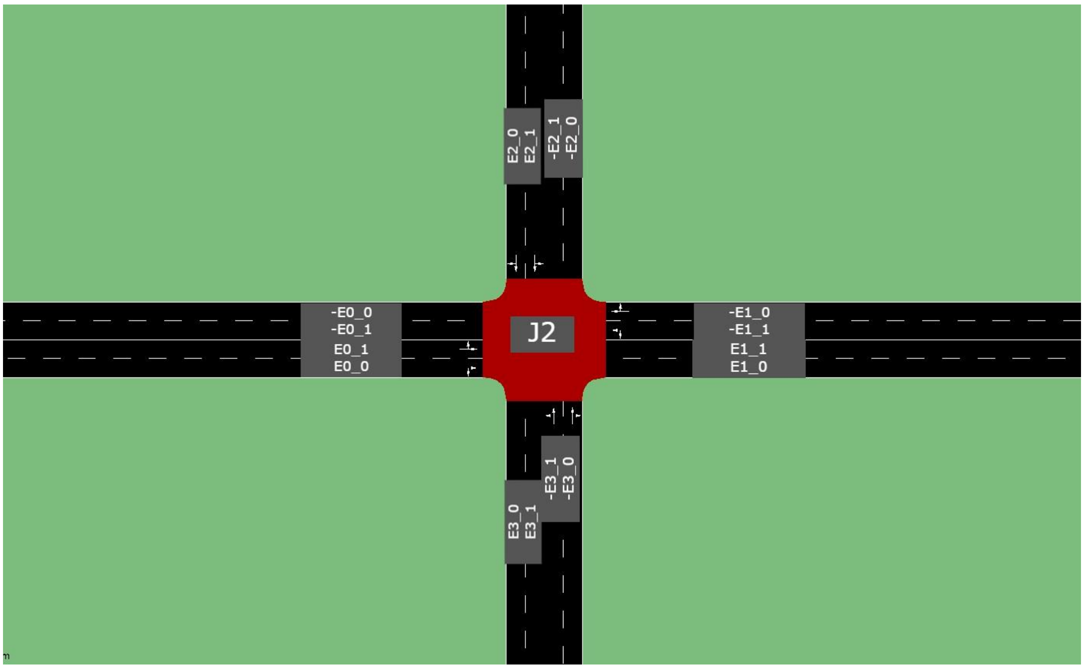
Simulation 1: Junction with traffic lights 2-lane 4-way intersection. [changing one parameter at a time] [30% not following rules]

Simulation 2: Junction with traffic lights 2-lane 4-way intersection. [changing one parameter at a time] [50% not following rules]

Simulation setup:

Step-length	0.10 sec (10 cycles/sec)
Collision.action	remove
Collision.stoptime	0 sec
Collision.check-junctions	True
'- - log' (simulation log files)	simulation_main.log
Number of Vehicles	500

2-Lane 4-Way Junction Details:



Parameters analyzed for the simulation studies:

Parameter	Range/value	Reason
jmDriveAfterRedTime (with jmDriveRedSpeed = 25 m/s)	[-1,0,1,2,4,5,6,8,9,10]	This value leads to vehicles disobeying a red traffic signal if the signal has

		turned red within the specified threshold period.
jmIgnoreFoeProb (with jmIgnoreFoeSpeed = 20 m/s)	[0.1,1.0] at step of 0.1	Probability at which it will ignore foe vehicle.
tau	[0.01,0.02,0.03,0.04, 0.05,0.06,0.07,0.08, 0.09,0.1,0.5,1.0]	Desired time headway
accel	[0.5,1,2,3,4,5,7,9,10,20]	Acceleration of vehicles
decel (with emergencyDecel = 5 m/s2)	[0.5,1,1.5,2,2.5,3,3.5,4,4.5,5]	Deceleration of vehicles (<= emergencyDecel)
sigmaerror	[0.1,0.2,0.3,0.4,0.5, 0.6,0.7,0.8,0.9,1.0]	Driving error magnitude
minGap	[1.5,2,2.5,3,3.5]	Empty space after leader [m]
speedFactor	[normc(0.8,0.1,0.2,1.5);normc(0.85,0.15,0.2,1.5); normc(1.0,0.15,0.2,1.5);normc(1.15,0.15,0.2,1.5); normc(1.2,0.2,0.2,1.5);normc(1.3,0.2,0.2,1.5)]	Speed distribution multiplier (mean,sd,min,max)
impatience	[0.1,0.2,0.3,0.4,0.5, 0.6,0.7,0.8,0.9,1.0]	Drivers' readiness to obstruct vehicles with higher priority
jmSigmaMinor	[0.1,0.2,0.3,0.4,0.5,0.6, 0.7,0.8,0.9,1.0]	driving imperfection (dawdling) while passing a minor link
lcCooperative	[1.0, 0.8, 0.6, 0.4, 0.2, -1]	willingness to perform cooperative lane changing
lcPushy	[0.1, 0.3, 0.5, 0.7, 0.9, 1.0]	Willingness to encroach laterally
lcSigma	[0.0, 0.1, 0.2, 0.3, 0.4, 0.5]	Lateral positioning-imperfection
lcSpeedGain	[0.5, 1.0, 1.5, 2.0, 2.5, 5.0]	eagerness for performing lane changing to gain speed
tpreview	[4,3,2,1.5,1]	Lower values result in late and hard braking when turning at junctions

Simulation 1: Junction with traffic lights 2-lane 4-way intersection. [changing one parameter at a time] [30% not following rules]

Experiment setup:

Fundamentally, it uses a set of probabilities, represented as the route_prob_range variable, to bring variability into the selection of vehicle routes. These probabilities, which are randomly set between 0.4 and 0.6, introduce an element of unpredictability to the simulation. The random_probability function is crucial in creating these random route probabilities, which are rounded to one decimal place, allowing for precise control over the chances of vehicles choosing particular routes.

```
route_prob_range = (0.4, 0.6)

def random_probability(prob_range):
    return round(random.uniform(*prob_range), 1)

xml_template = f"""<?xml version="1.0" encoding="UTF-8"?>
<routes xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance" xsi:noNamespaceSchemaLocation="http://sumo.dlr.de/xsd/routes_file.xsd">
    <!-- VTypes -->
    <vTypeDistribution id="vd1">
        <vType id="ego_veh" guiShape="passenger" carFollowModel="EIDM" color="red" probability="0.3" />
        <vType id="default" guiShape="passenger" carFollowModel="Krauss" color="yellow" probability="0.7" />
    </vTypeDistribution>

    <!-- Routes -->
    <routeDistribution id="rd1">
        <route id="r_0" edges="-E1 -E0" probability="{random_probability(route_prob_range)}"/>
        <route id="r_1" edges="E0 E1" probability="{random_probability(route_prob_range)}"/>
        <route id="r_10" edges="-E3 E1" probability="{random_probability(route_prob_range)}"/>
        <route id="r_11" edges="-E1 -E2" probability="{random_probability(route_prob_range)}"/>
        <route id="r_2" edges="-E3 -E2" probability="{random_probability(route_prob_range)}"/>
        <route id="r_3" edges="E2 E3" probability="{random_probability(route_prob_range)}"/>
        <route id="r_4" edges="-E1 E3" probability="{random_probability(route_prob_range)}"/>
        <route id="r_5" edges="E2 E1" probability="{random_probability(route_prob_range)}"/>
        <route id="r_6" edges="E0 -E2" probability="{random_probability(route_prob_range)}"/>
        <route id="r_7" edges="-E3 -E0" probability="{random_probability(route_prob_range)}"/>
        <route id="r_8" edges="E2 -E0" probability="{random_probability(route_prob_range)}"/>
        <route id="r_9" edges="E0 E3" probability="{random_probability(route_prob_range)}"/>
    </routeDistribution>

    <flow id="myflow" type='vd1' route='rd1' begin="0" end="500" number="500">
    </flow>
</routes>
"""
```

This XML template incorporates two essential components: vehicle types and routes. Under the <vTypeDistribution> section, "ego_veh" with EIDM car-following model and "default" with Krauss car-following model vehicle types are defined, each assigned a 30% and 70% probability respectively. These types govern vehicle appearance and behavior within the simulation. Meanwhile, the <routeDistribution> section details various vehicle routes, specifying the edges that vehicles will traverse, and leverages the random_probability function to allocate random route probabilities.

Finally, a traffic flow named "myflow" is established, utilizing the defined vehicle types and routes, along with temporal parameters, to simulate the flow of 500 vehicles within the controlled traffic environment.

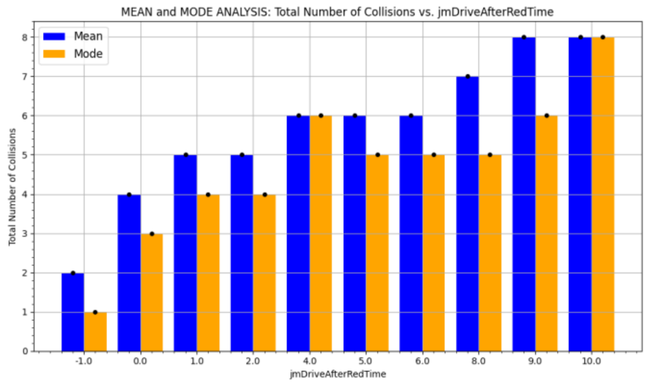
Each parameter value underwent 10 simulation runs, and the results were subsequently aggregated, averaged, or analyzed for that specific parameter. The results of the overall simulation of each parameter were saved in a JSON file, making it convenient to extract relevant information.

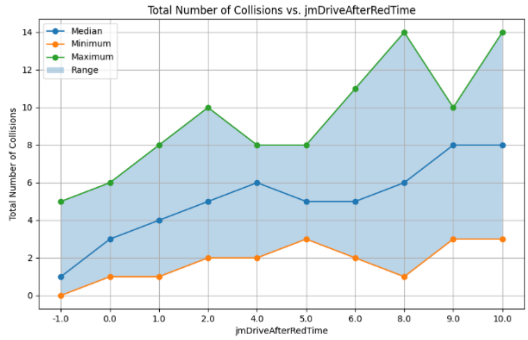
Results:

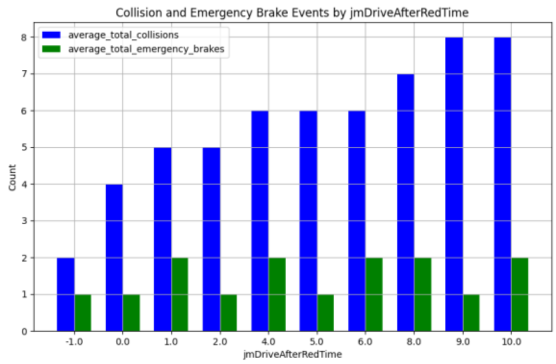
When conducting the simulation with a distribution of 30% ego vehicles and 70% default vehicles, we identified several critical parameters that have the potential to lead to collisions. These parameters include:

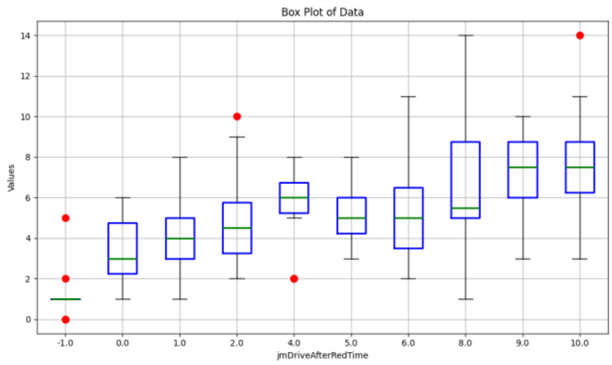
jmDriveAfterRedTime (with jmDriveRedSpeed = 25 m/s):

The simulation results show that increasing the jmDriveAfterRedTime parameter generally leads to more collisions particularly at higher values (8 to 10), while zero and negative values of this parameter reduce collisions to some extent. There is variability in collision outcomes, and median and mode values provide insights into the central tendencies of the data.

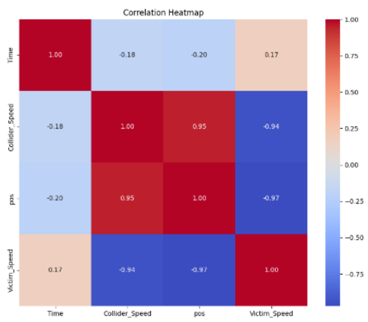


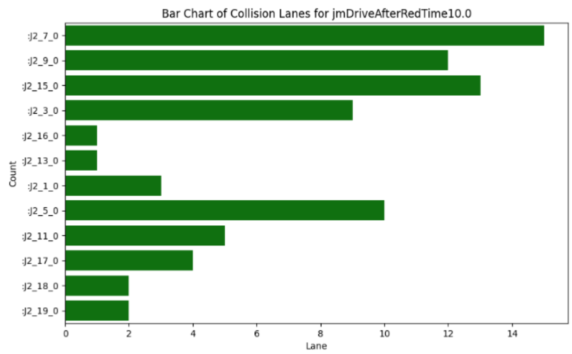


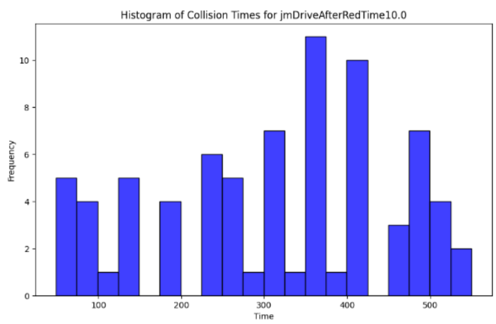


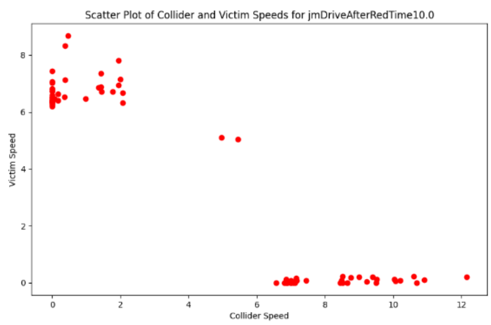


The data shows variability in collision results for the same jmDriveAfterRedTime values. For example, for a jmDriveAfterRedTime of 4, the number of collisions can range from 2 to 8, as indicated by the range in min and max values of collision. Below are the plots at jmDriveAfterRedTime = 10s which has the maximum average collisions of 8. Most of the collisions are junction collision as it is a junction safety parameter. As seen from the correlation plot we can see a negative correlation between collider and victim speeds. We can also see that maximum collisions happen between 300 to 400 seconds.



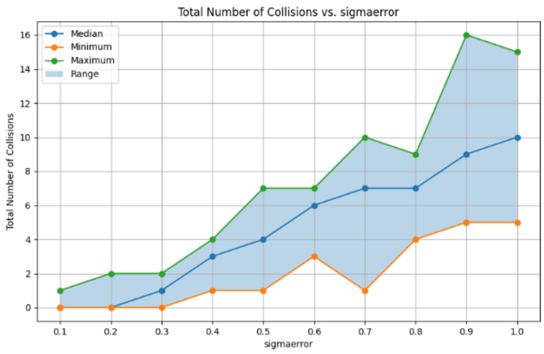


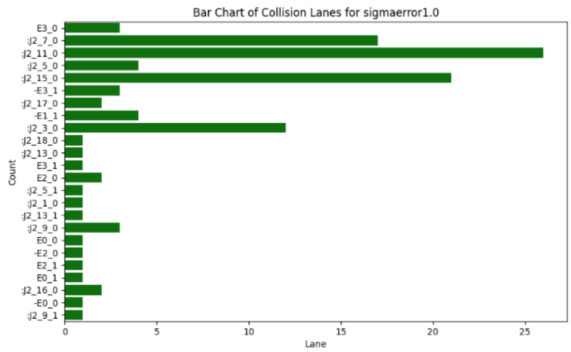


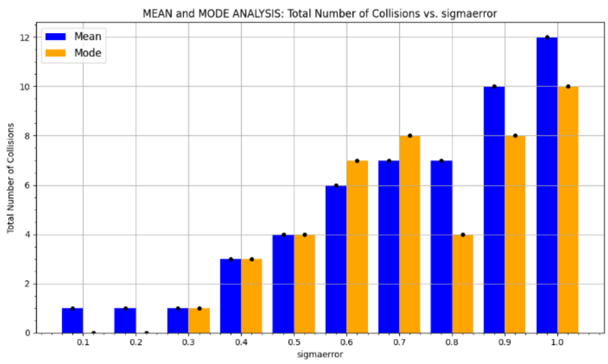


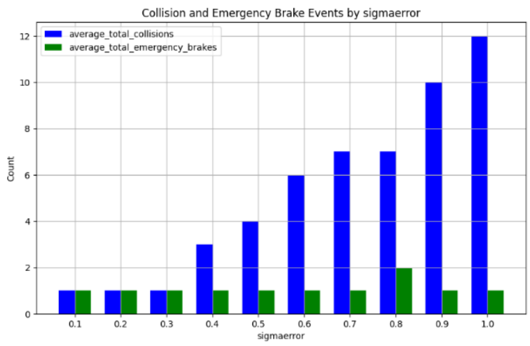
sigmaerror:

Higher sigma error values (driving error magnitude) correlate with increased collision rates across all statistical central tendencies. This simulation included collisions that occurred both at junctions and within lanes. Mode shows the most variation with sigma error, suggesting it's sensitive to driving error changes and may reflect the frequency of common collision scenarios. The max-min plot illustrates the potential collision range for each parameter value.

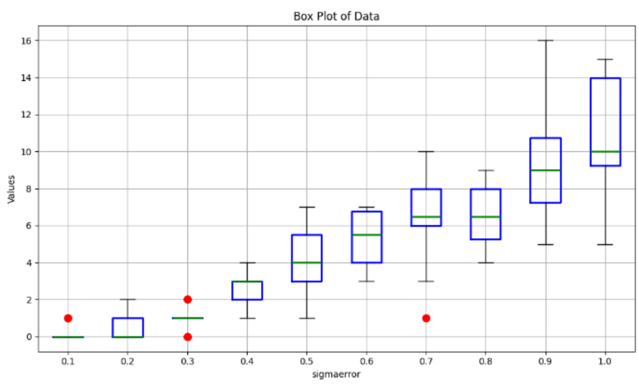


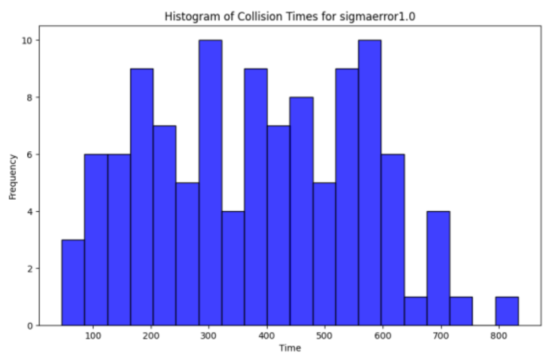


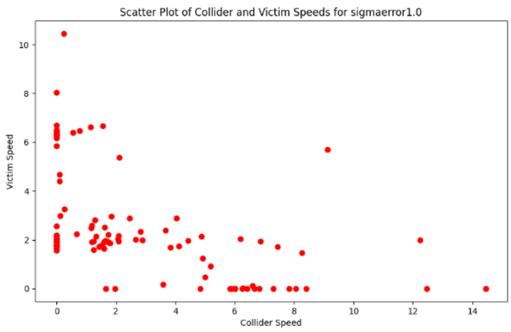


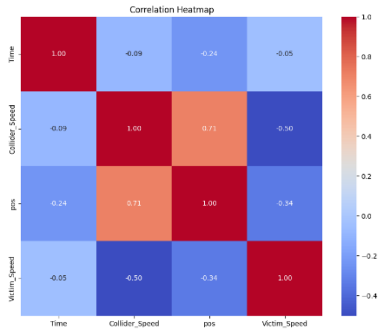


The maximum collision happened at 1 sigma error with 12 collisions. The collisions are equally distributed across the simulation time, making it a crucial parameter for accidents. The relationship between sigma error (driving error magnitude) and various collision parameters, offers insights into how different aspects of vehicle collisions are affected by changes in driving error.



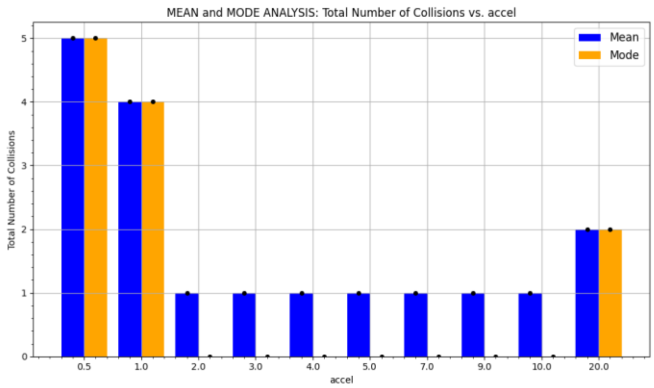


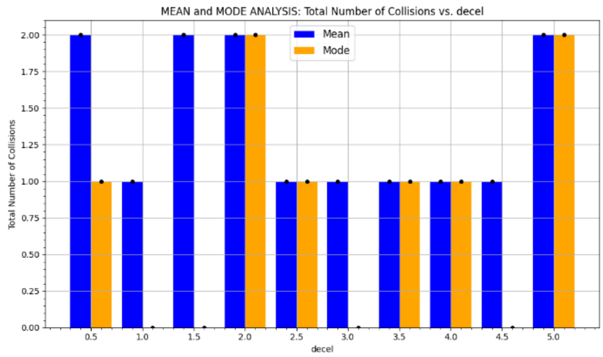


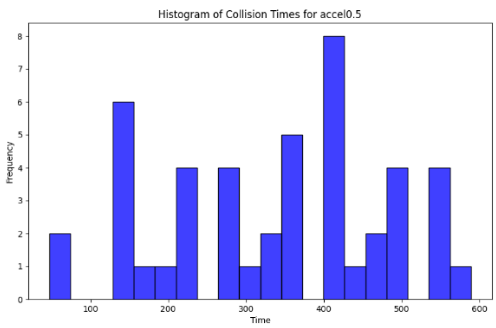


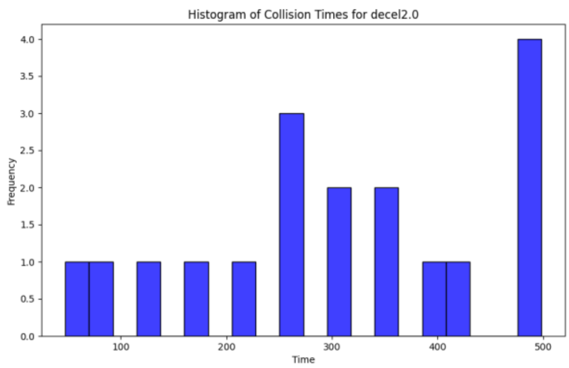
accel and decel ((with emergencyDecel = 5 m/s2)):

Increasing the acceleration of vehicles leads to a decrease in the number of collisions at junctions but it increases when the acceleration value is very high i.e., 20 m/s2. This is because vehicles with higher acceleration can clear intersections more swiftly, lowering the likelihood of collisions. In the case of vehicle deceleration, it's evident that there is a maximum of 2 collisions, and the collision values for mean and mode remain constant even at higher deceleration values. Additionally, collisions over time peak at approximately 400 seconds for the acceleration parameter and around 480 seconds for the deceleration parameter.



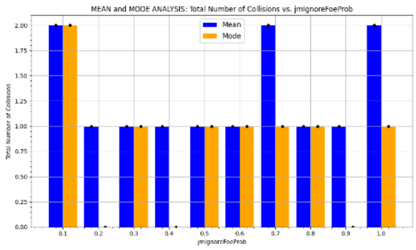


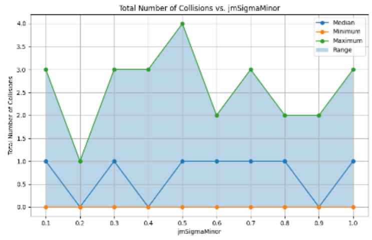


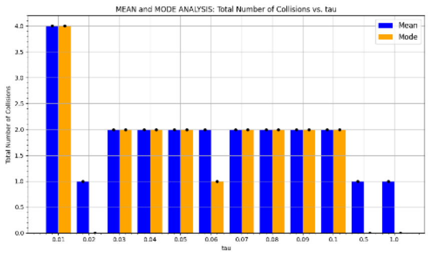


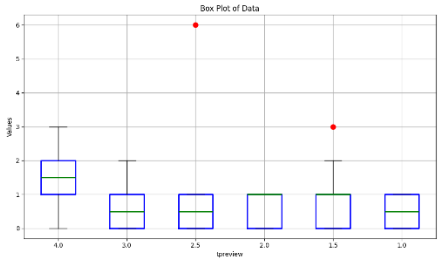
Other parameters: The lane-changing parameters resulted in a few collisions, but these collisions weren't primarily associated with lane changes; instead, they were more often linked to rear-end and junction collisions. For other junction-related parameters such as jmIgnoreFoeProb and jmSigmaMinor, they exhibited a maximum of 2 to 3 collisions. Parameters like impatience and tpreview only led to one collision among 500 simulated vehicles. The tau values demonstrated a significant number of collisions, and there was a negative correlation observed as parameter values increased.

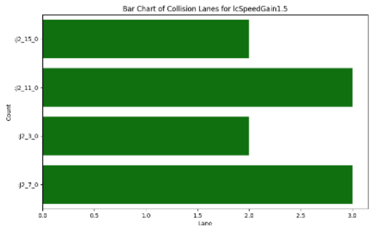
Some other parameter plots:

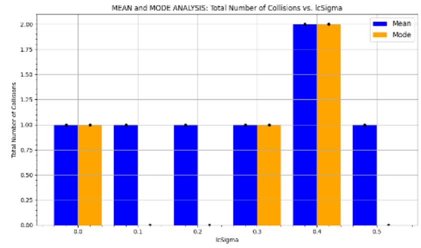












Simulation 2: Junction with traffic lights 2-lane 4-way intersection. [changing one parameter at a time] [50% not following rules]

Experiment setup:

The simulation setup is identical to Simulation 1, except for a modification in the probability of the ego vehicle (ego_veh) and the default vehicle to 0.5.

```
route_prob_range = (0.4, 0.6)

def random_probability(prob_range):
    return round(random.uniform(*prob_range), 1)

xml_template = f"""<?xml version="1.0" encoding="UTF-8"?>
<routes xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance" xsi:noNamespaceSchemaLocation="http://sumo.dlr.de/xsd/routes_file.xsd">
    <!-- VTypes -->
    <vTypeDistribution id="vd1">
        <vType id="ego_veh" guiShape="passenger" carFollowModel="EIDM" color="red" probability="0.5" />
        <vType id="default" guiShape="passenger" carFollowModel="Krauss" color="yellow" probability="0.5" />
    </vTypeDistribution>

    <!-- Routes -->
    <routeDistribution id="rd1">
        <route id="r_0" edges="-E1 -E0" probability="{random_probability(route_prob_range)}"/>
        <route id="r_1" edges="E0 E1" probability="{random_probability(route_prob_range)}"/>
        <route id="r_10" edges="-E3 E1" probability="{random_probability(route_prob_range)}"/>
        <route id="r_11" edges="-E1 -E2" probability="{random_probability(route_prob_range)}"/>
        <route id="r_2" edges="-E3 -E2" probability="{random_probability(route_prob_range)}"/>
        <route id="r_3" edges="E2 E3" probability="{random_probability(route_prob_range)}"/>
        <route id="r_4" edges="-E1 E3" probability="{random_probability(route_prob_range)}"/>
        <route id="r_5" edges="E2 E1" probability="{random_probability(route_prob_range)}"/>
        <route id="r_6" edges="E0 -E2" probability="{random_probability(route_prob_range)}"/>
        <route id="r_7" edges="-E3 -E0" probability="{random_probability(route_prob_range)}"/>
        <route id="r_8" edges="E2 -E0" probability="{random_probability(route_prob_range)}"/>
        <route id="r_9" edges="E0 E3" probability="{random_probability(route_prob_range)}"/>
    </routeDistribution>

    <flow id="myflow" type='vd1' route='rd1' begin="0" end="500" number="500">
    </flow>
</routes>
"""
```

Each parameter value underwent 10 simulation runs, and the results were subsequently aggregated, averaged, or analyzed for that specific parameter. The results of the overall simulation of each parameter were saved in a JSON file, making it convenient to extract relevant information.

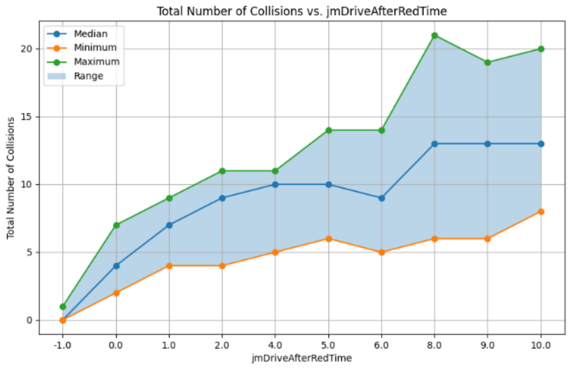
Results:

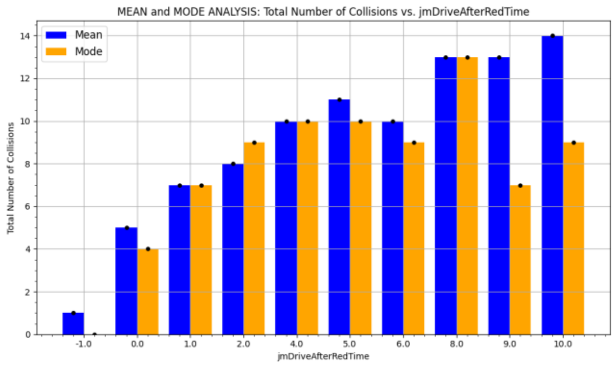
When conducting the simulation with a distribution of 50% ego vehicles and 50% default vehicles, we identified several critical parameters that have the potential to lead to collisions. These parameters include:

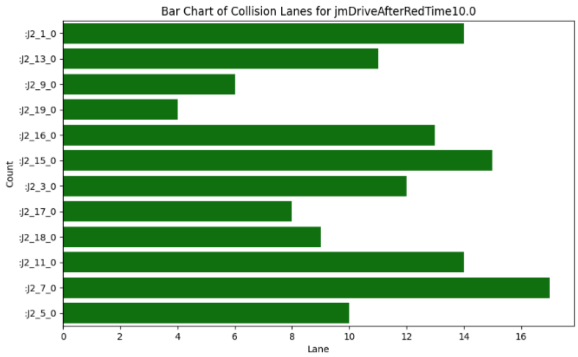
jmDriveAfterRedTime (with jmDriveRedSpeed = 25 m/s):

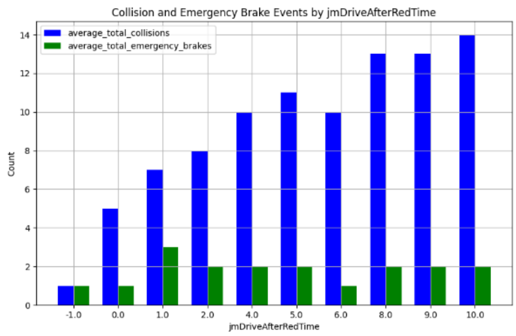
The simulation findings indicate that raising the jmDriveAfterRedTime parameter typically results in an increased number of collisions, especially at higher values. In contrast, setting this parameter to zero or using negative values reduces collisions to some extent.

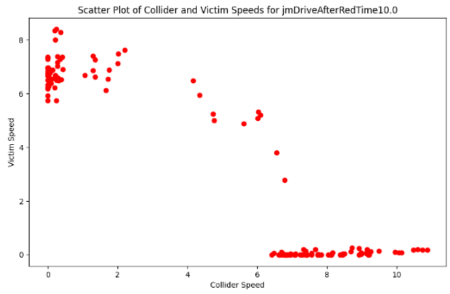
Notably, there's a significant rise in collision count when the probability of the ego vehicle is increased. At a 0.3 probability, the maximum number of collisions reached 8, while at a 0.5 probability, it peaked at 14. This increase is particularly pronounced in junction collisions. The pattern observed at a 30% ego vehicle probability remains consistent for the jmDriveRedTime parameter as well.

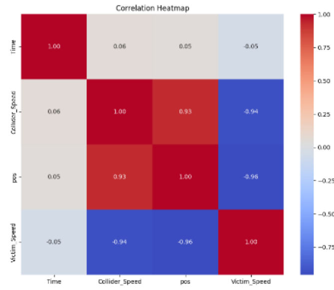


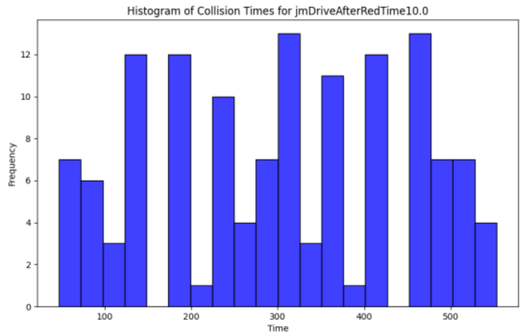


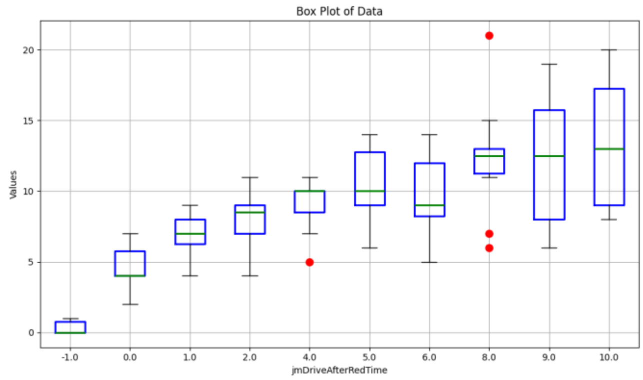






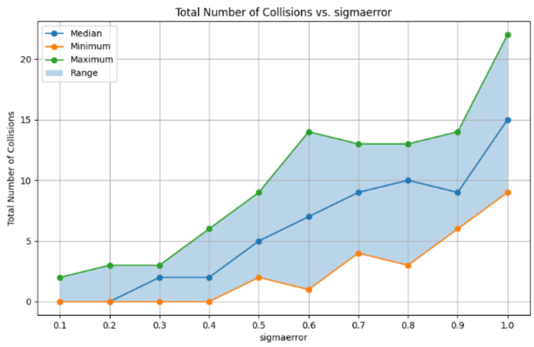


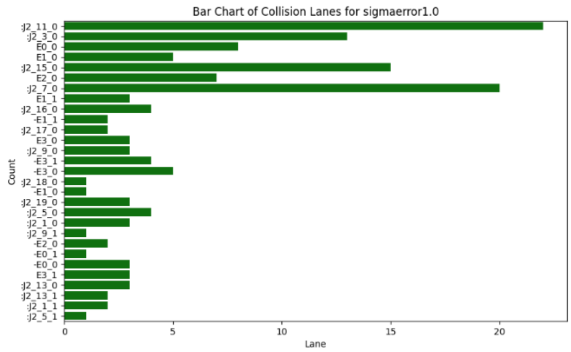


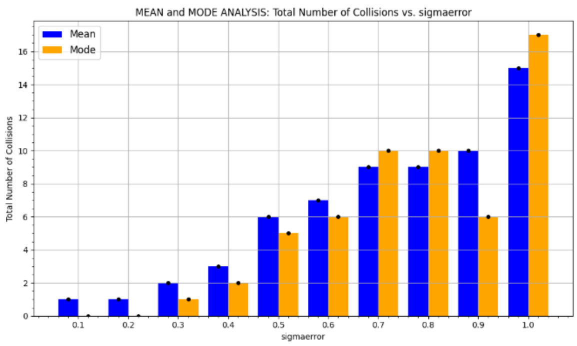


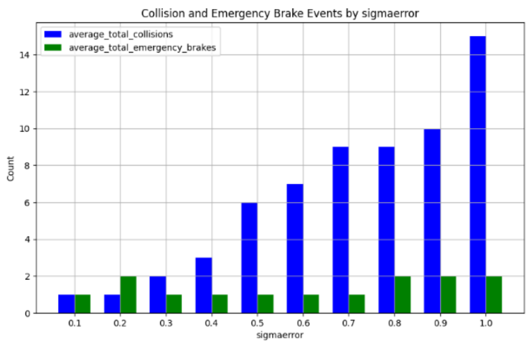
Sigmaerror:

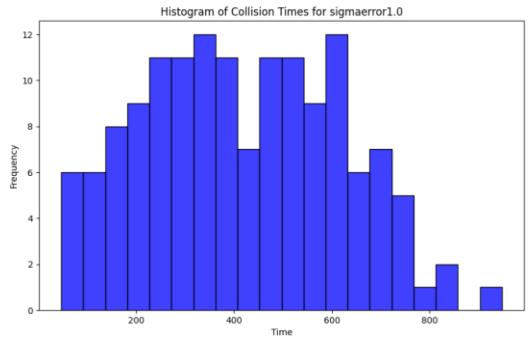
There is a positive correlation of sigma error with the number of collision, as sigma error denotes driver imperfection parameter. Compared to 30% eqo vehicles there is a rise of number of collisions from 12 to 16. Compared to Simulation 1 there are number of collision lanes as seen from their bar charts.

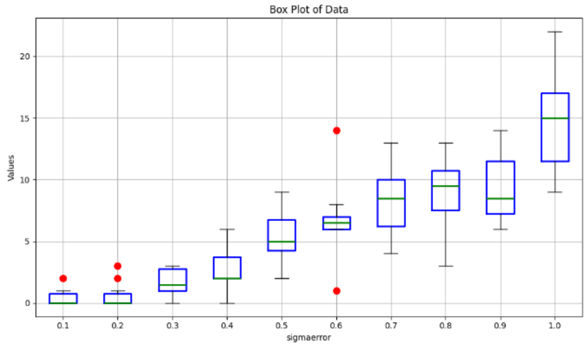


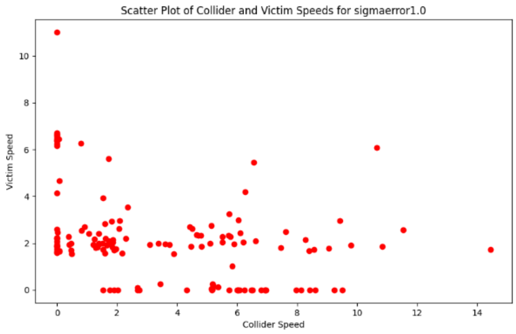


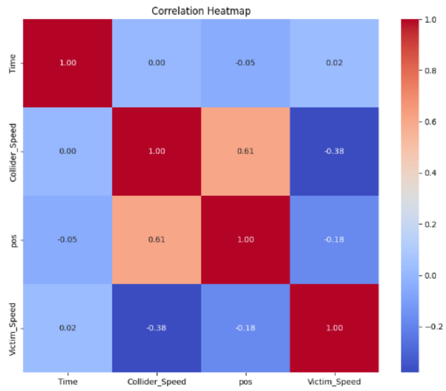






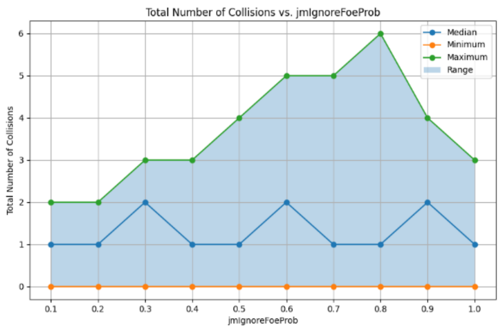


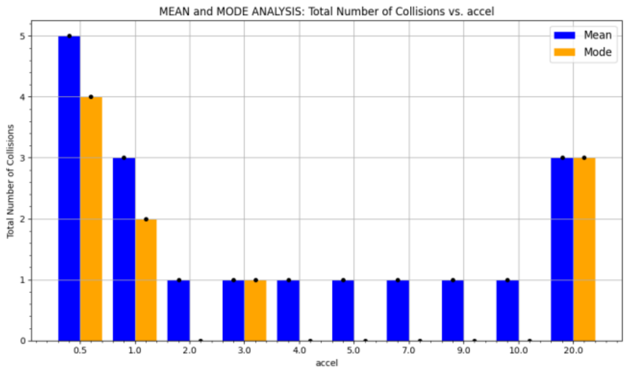


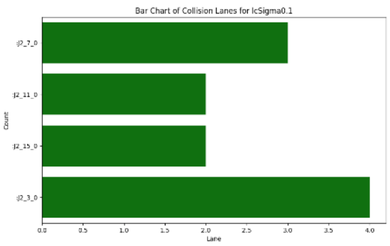


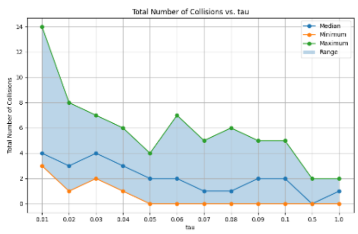
The remaining parameters exhibited a consistent trend as observed with 30% ego vehicles, with the exception of an increase in the number of collisions.

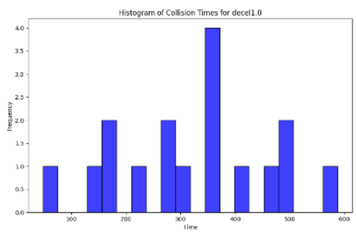
Some parameter plots:











PART-2: Vehicle Actions and Their Influence on Other Traffic Participants

I carried out two simulations, one utilizing the parameters described in the research paper titled "Simultaneous Policy Learning and Latent State Inference for Imitating Driver Behavior," and the other based on the univariate analysis mentioned earlier.

Simulation setup:

Step-length	0.10 sec (10 cycles/sec)
Collision.action	remove
Collision.stoptime	0 sec
Collision.check-junctions	True
'- - log' (simulation log files)	simulation_main.log
Number of Vehicles	100
Number of runs	10
probability of each vehicle type to appear	0.25

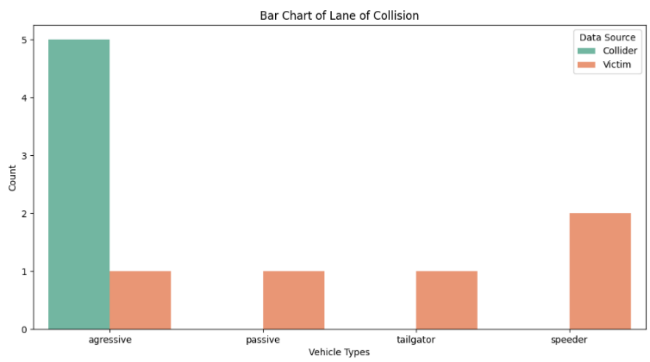
Research Paper implementation:

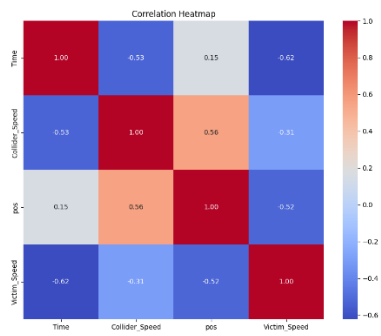
	maxSpeed m/s	minGap m	tau	Accel m/s2	Decel m/s2
Passive	10	5	1.75	1	1
Aggressive	30	1	0.25	5	5
Tailgater	15	1	0.25	1	1
Speeder	30	5	1.75	5	5

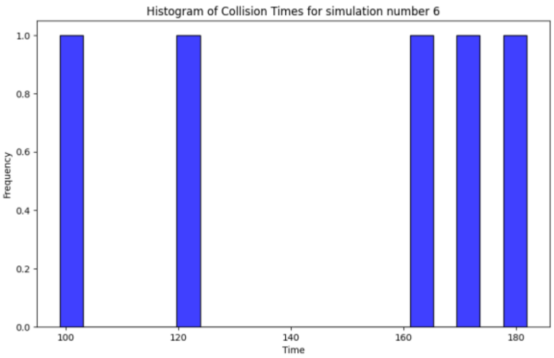
"Passive" drivers like to drive slowly, keep a lot of space between cars, and accelerate gently. "Aggressive" drivers prefer going fast, driving close to others, and accelerating quickly. "Tailgaters" are like passive drivers but are willing to drive closer to the car in front while going a bit faster. "Speeders" are like aggressive drivers but maintain more distance from the car in front, being careful not to tailgate.

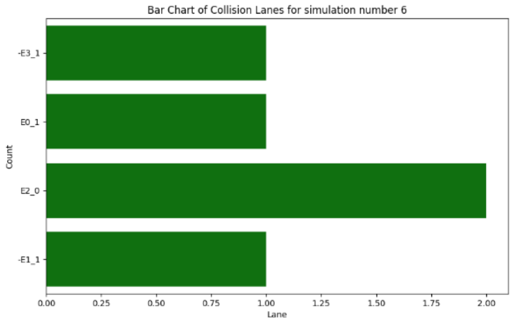
Results:

On implementing the research paper parameters for 100 vehicles, we found that aggressive drivers are the primary culprits in causing accidents, with speeders being the most common victims of these accidents.









It can be observed from the Collision times plot that the major number of accidents happened between 160 to 180 seconds. Most of the collisions caused by this configuration is rear-end lane collisions.

The 10 simulation run results reveal that the average number of collisions in the simulation is around 3, and the median value, with 3 being the midpoint. The standard deviation of approximately 1.89 i.e. 2 collisions suggests that there is some variability or spread in the number of collisions. The range between 0 and 6 encompasses the full spectrum of potential collision outcomes. The interquartile range (IQR) from 2 to 4 provides a more focused view of where the bulk of the collisions lie.

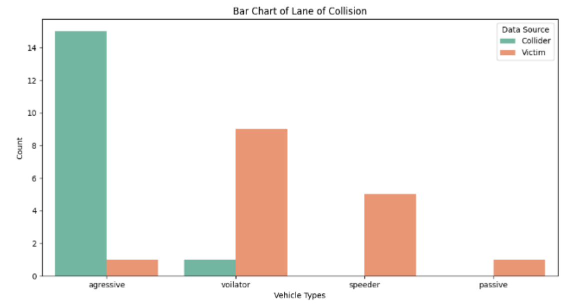
Modified Implementation:

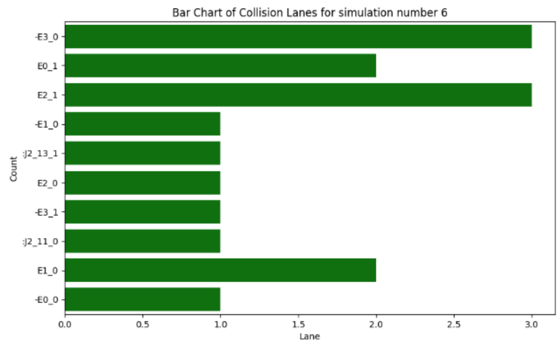
Passive	Tau = 1.75, minGap = 2.5 m, accel = 1 m/s2, decel = 1 m/s2, maxSpeed = 10 m/s
Aggressive	Tau = 0.25, minGap = 1 m, accel = 5 m/s2, decel = 5 m/s2, maxSpeed = 60 m/s, sigmaerror = 0.5, emergencyDecel = 5 m/s2
Violator	Tau = 0.25, minGap = 2 m, accel = 1 m/s2, decel = 5 m/s2, maxSpeed = 40 m/s, sigmaerror = 0.9, jmDriveRedSpeed =25 m/s, jmDriveAfterRedTime = 10 sec, emergencyDecel = 5 m/s2
Speeder	Tau = 1.75, minGap = 2.5 m, accel = 5 m/s2, decel = 5 m/s2, maxSpeed = 60 m/s, emergencyDecel = 5 m/s2

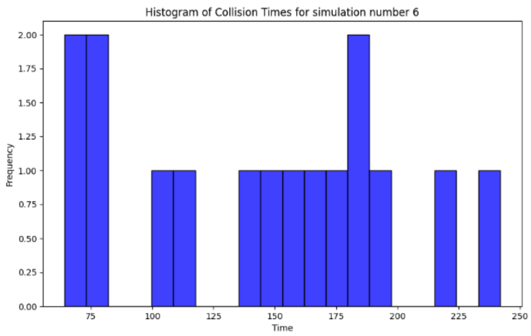
"Passive" drivers like to drive slowly, keep a lot of space between cars, and accelerate gently. "Aggressive" drivers prefer going fast, driving close to others, little imperfect driving, and accelerating quickly. "Voilator" drivers who try to skip red lights, has a high max speed, keep low space between cars, and are imperfect driver. "Speeders" are like aggressive drivers but maintain more distance from the car in front, being careful not to tailgate.

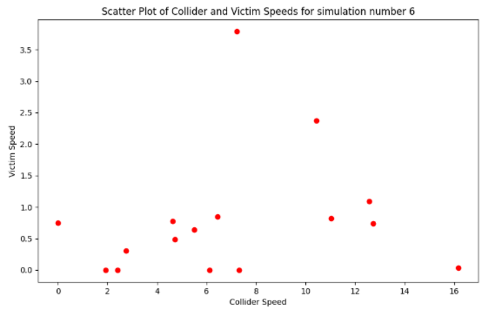
Results:

After making adjustments to the parameters and vehicle types following a univariate analysis, our findings revealed that aggressive drivers are primarily responsible for causing accidents, resulting in a total of 15 collisions. Violators, who tend to break traffic rules, emerged as the most frequent victims of these accidents, typically instigating issues on the road. This modified configuration led to a combination of rear-end lane collisions and junction collisions. Notably, a significant portion of these collisions occurred within the timeframe of 140 to 200 seconds.









The results from 10 simulation runs indicate that the average collision count is approximately 12, with 13 being the median. There is some variability in collision numbers, as the standard deviation is around 3.44 i.e. 4, meaning that the results can deviate from the average by about 3.44 collisions on average. The range of collisions spans from 6 to 16, covering a wide spectrum of possible outcomes. The interquartile range (IQR), which falls between 11 and 14, offers a narrower view of where most collision counts are concentrated.

Comparison:

The initial implementation of the research paper parameters for 100 vehicles highlighted aggressive drivers as the primary causes of accidents, predominantly resulting in rear-end lane collisions, with a concentration of accidents occurring between 160 to 180 seconds. This configuration led to an average of 3 collisions, with a standard deviation of approximately 1.89, suggesting moderate variability. The modified implementation, following univariate analysis and parameter adjustments, reinforced the dominance of aggressive drivers in causing accidents, but the total collision count increased significantly to 15, mainly involving violations of traffic rules and a mix of rear-end lane and junction collisions. The collision times shifted slightly, occurring within 140 to 200 seconds. In this modified setup, the average collision count rose to 12, with a median of 13 and a higher standard deviation of about 3.44, indicating greater variability.

Overall, the modified implementation revealed a substantial increase in accidents and greater variability in collision counts compared to the initial implementation, emphasizing the impact of parameter adjustments on simulation results.